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The impact of climate funds on economic growth and their role in substituting fossil energy sources[☆]

Alfonso Carfora[a,*], Giuseppe Scandurra[b]

[a] Italian Revenue Agency, Via Cristoforo Colombo, 426 00145 Rome, Italy
[b] Department of Management Studies and Quantitative Methods, University of Naples "Parthenope", via Generale Parisi, 13, Naples I-80132, Italy

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ABSTRACT

In recent years, the climate funds stood out as tool to counter the climate change and its environmental impact financing adaptation. Moreover they represent an instrument to promote practices to support the developing countries in their path towards the sustainability.

The aim of this paper is to evaluate the effectiveness of the introduction of policies implementing the use of climate funds. To reach it we analyze the funds received by the recipient through a counterfactual analysis. The results show that the policy contributed to the decreasing of greenhouse gas (GHG) emissions and promoted the change in generation energy systems supporting the replacement of fossil sources with renewable sources. Moreover, in these countries highlights the leverage effect of the climate finance for the economic development.

1. Introduction

During the 15th Conference of the Parties (COP15) held in December 2009 in Copenhagen, developed countries pledged to provide new and additional resources to combat climate change, approaching USD 30 billion for the 2010–2012 period, with balanced allocation between mitigation and adaptation strategies. This collective commitment is known as 'fast-start finance' and prefigures the institution of the Green Climate Fund (GCF)[1] established by the 194 countries that are members of the United Nations Framework Convention on Climate Change (UNFCCC) in 2010, to support a paradigm shift in the global response to climate change.

Through the GCF mechanism, donor governments distribute funds to recipient developing countries to finance low-emissions and climate-resilient projects and programs in these countries. As they are proliferating, the challenges of coordinating funds and the monitoring of recipient countries' emissions became an important matter to assess their effectiveness.

In this paper, we want to evaluate the impact of the climate funds distributed by donor countries on environmental and economic factors. To reach this aim we analyze the flow of funds among countries and conduct a counterfactual analysis to assess and quantify the effectiveness of climate funds following three sub-questions: i) have the recipient countries achieved the objectives of greenhouse gases (GHG) emission reduction for which the funds were granted? ii) Are these funds useful for the countries in incentivizing the replacement of fossil sources with renewable sources? iii) Is there a leverage effect for economic development?

To achieve our aims, we employ propensity score matching (PSM) analysis on a large dataset of 149 countries[2] that includes countries that have received funds in 2010 (treated – 83 counties) and those that have not received funds (untreated – 66 countries). PSM is a statistical method which make the construction of a probabilistic match among units that have participated in a treatment (treated) and units that have

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* Corresponding author.
E-mail addresses: alfonso.carfora@uniparthenope.it (A. Carfora), giuseppe.scandurra@uniparthenope.it (G. Scandurra).

[1] The GCF is a financial mechanism to reduce greenhouse gas emissions in developing countries. It was funded within the framework of the UNFCCC with the aim of assisting developing countries in adaptation and mitigation practices to counter climate change. The objective is pursued supporting and financing projects, programs, policies and other activities in developing countries using thematic funding windows. The GCF pays particular attention to the needs of societies that are highly vulnerable to the effects of climate change, in particular Least Developed Countries (LDC), Small Island Developing States (SIDS), and African States.

[2] To assess the impact of "fast-start finance," the dataset refers to the AidData Research Release 2.1 (of which the last year is 2010) because the disbursements are not made available in the new release of the AidData (Released: 2016/04/29), which includes commitments that are not sufficient for evaluating the impact of this policy measure.

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not participated (untreated), utilizing characteristics that are common to both groups (Rosenbaum and Rubin, 1983). The results of the econometric analysis contribute to the literature on the climate change because can be helpful in determining the effectiveness of the climate mechanism in terms of: i) promoting renewable energy sources (RES) generation; ii) combating climate change; iii) reducing the impact of anthropogenic activities on the environment.

The remainder of the paper is organized as follows: a brief literature review is exposed in Section 2, Section 3 reports the methodology employed, whereas Section 4 describes the data. Section 5 reports the empirical results while in Section 6 we discuss the results. Finally Section 7 offers some concluding remarks.

2. Brief literature review

The literature about climate finance involves two major aspects: the former studies the funds' managing individuating the different drivers that underlie the aid allocation, the latter analyzes a less explored field: the effectiveness of climate finance.

In the first context a critical issue is the transparency of the implementation of climate finance initiatives; consequently the political and institutional relationships become a very important issue to be considered. The OECD, in collaboration with Climate Policy Initiatives (OECD, 2015), provided a status check on the level of climate finance mobilized by developed countries in 2013 and 2014 finding that there are closed to 100 billion USD. Brunner and Enting (2014) and Pickering et al. (2015) argue the need for collaboration between development and environmental agencies to manage the funds of climate finance and avoid disagreements about priority targets. The international cooperation on finance has the potential to help countries to manage such tradeoffs and create new incentives for low-carbon development. Although global climate finance is still fragmented (Pickering et al., 2017) and heterogeneous it can support policies to improve resilience against the threats of the climate change (Nakhooda and Norman, 2014) but the allocation of resources to developing countries should be guided by clear goals and sector-specific or hazard-specific criteria (Füssel, 2010). As highlighted by Tol (2017) and Nakhooda and Norman (2014), disparities among governments' priorities between environmental issue and a rapidly economic growth would make any opportunity of expansion of climate policy unsuccessful.

Among the authors that analyze the drivers leading the fund's allocation, Bandyopadhyay and Wall (2007) show that the aid allocation has a negative relationship with GDP per capita and positive with infant mortality, rights, and government effectiveness whereas Alesina and Dollar (2000) assess that foreign aid allocations were linked to political and strategic considerations of donor countries.

In the second context, the main issue is the analysis of the impact of the climate funds on their environmental and economic targets. Ellis et al. (2013) explore how different communities view climate finance effectiveness, the policies or institutional pre-conditions that facilitate effectiveness, and how effectiveness is currently monitored and evaluated. Bird et al. (2013) describe an approach to measuring the effectiveness of the national systems that support climate finance delivery. They assess three interlinked elements of government administration: the policy environment, which supports climate change expenditures; the institutional architecture, which determines the relevant roles and responsibilities; and the public financial system, through which climate change-related expenditures are channeled.

Betzold and Weiler (2017) analyze as the countries that are more exposed to climate change received more adaptation aid while Scandurra et al. (2017) highlight the strong heterogeneity in the funds' distribution. They underline that European countries seem to focus on commercial partners and concentrate their funds in specific recipient countries, unlike the USA and Japan, which have allocated their aid (in lower amounts than some European countries) across various and different projects intended for many developing countries. In a recent paper, Carfora et al. (2017) find that funds directed to "fast-start finance" meet the requirements of ensuring the reduction in GHG and promoting the sustainable development of developing countries. To improve the effectiveness of climate funds, they suggest redesigning aid schemes not only to combat climate change but also to promote resilience to extreme events and to reduce dependence on preferential channels with developed countries.

3. Theory and methods

The aim of climate finance is the promotion of green growth and, consequently, a reduction in GHG emissions. Thus, we want to investigate whether there are systematic differences between groups of countries in a set of environmental, energy and economic target variables. Whether these differences exist, we want to quantify their magnitude using a counterfactual analysis. The analysis is conducted to compare the ex post realized outcome of the treated countries with a counterfactual outcome of the untreated countries that, under certain assumptions, reproduces the ex ante situation.

Counterfactuals have been previously used to examine a range of statistical and macroeconometric questions. An examples of macro counterfactuals is the paper of Abadie and Gardeazabal (2003), in which the authors investigate about the economic effects of conflict, using the terrorist conflict in the Basque Country as a case study. Pesaran and Smith (2016) examine the effects of the quantitative easing introduced in the UK after March 2009. Hsiao, Ching and Wan (2011) study the effect of political and economic integration with mainland China on output growth in Hong Kong, constructing counterfactuals based on predictions from similar economies. In some recent works, PSM is used concerning macro policy evaluation borrowing techniques from the micro literature to obtain an estimate of an average treatment effect. Angrist, Jorda and Kuersteiner (2017), drawing on a previous work (Angrist and Kuersteiner, 2011), estimate the effect of monetary policy using three samples each of them equal to 24 monthly observations of the federal funds rate futures. They measure the average effect of policy changes on future values of the outcome variables (inflation, industrial production, and unemployment), inversely weighted by policy propensity scores in a manner similar to that used to adjust non-random samples. With similar procedures Jorda and Taylor (2013) estimate the effect of fiscal policy on GDP using five years timely observations. Romano et al. (2016) investigate some specific features related to the energy policy choices of countries, based on the comparison and matching of variables drawn from a macroeconomic panel dataset of 56 countries observed in the years from 2004 to 2011.[3]

Let us consider that the treatment indicator, I_i, is equal to *1* if individual *i* receives the treatment and otherwise *0*. The match is made according to the values of a score, i.e. the propensity score, which consists in the probability of an individual being assigned to a treatment given a set of observed covariates (control variables). One possible identification strategy is to assume that, given a set of observable covariates X, which are not affected by the treatment, the potential outcomes are independent of the treatment assignment and any systematic differences in outcomes between treated and control group are attributable to treatment. The implication is that selection is solely based on observable characteristics and that all variables that influence the treatment assignment and potential outcomes are observed simultaneously. A further requirement besides independence is the common support or overlap condition. It ensures that countries with the same X values have a positive probability of being both participants and

[3] Generally, Propensity Score Matching works with micro data and this allows for higher numbers of statistical units. However, the countries analyzed in this paper represent the totality of countries eligible to receive funds according to the OECD's Official Development Assistance (ODA) list. This reduces the possibility of having larger databases.

non-participants (Heckman et al., 1999).

The application of the PSM technique requires the execution of several sequential steps (Rubin, 1997):

1. A variable indicator I_i is fixed for each individual, assuming the value of 1 if the individual results as being treated and otherwise 0.
2. The evaluation of a probit/logit regression model of the following type:

$$\pi_i = \alpha + \sum_{j=1}^{k} \beta_j x_{ij} \tag{3.1}$$

3. The creation of a vector of the propensity scores composed of *i*-scalers, each of which is equal to the following

$$p_i = \Phi(\pi_i) = Prob(I_i = 1 \mid X) \tag{3.2}$$

where φ(.) is the cumulative distribution function (*cdf*) of a normal distribution (if one has chosen to estimate the scores with a probit model) or a logistic distribution (if one has chosen to estimate the scores with a logit model) and X is the vector of the covariates included in the model as control variables. It ensures that individuals with the same X values have a positive probability of being both participants and non-participants (Heckman et al., 1999).
4. The matching, based on the similarity of the scores, of the individuals treated with those untreated.

The most frequently utilized *matching* method is *nearest neighbor matching* (Rosenbaum and Rubin, 1983). This procedure consists of matching to each treated individual another untreated individual who has the nearest numerical propensity score.

Once the match has been made, the parameter that received the most attention in the evaluation literature is the average treatment effect on the treated (ATT), which is defined as follows:

$$ATT_i = E(t_i \mid I = 1) = E[(Y_i(1)I = 1) - E[(Y_i(0)I = 1) \tag{3.3}$$

where Y(1) represents the value of the variable Y of the *i-th* individual exposed to the treatment and Y(0) represents the value of the same variable for the same individual in the absence of treatment. Because the counterfactual expected value $E[(Y_i(0)I = 1)$ is not observed for the treated, it is approximated with the value of the most similar *j-th* individuals in terms of the propensity scores. Eq. (3.3) becomes:

$$ATT_i = E[(Y_i(1)I = 1) - E[(Y_i(0)I = 1) = t_{ATT} + \quad E[(Y_i(1)I = 1) - E[(Y_j(0)I = 0) \tag{3.4}$$

The difference between the left-hand side of Eq. (3.4) and t_{ATT} is the so-called self-selection bias that is not observed; the lower it is, the better defined is the propensity score model.

The algorithm that serves as the basis of *nearest neighbor matching* ensures that each untreated individual, once he or she is matched, is reinserted into the procedure to be possibly matched to another treated individual that is, however, numerically near it (based on a predefined margin). For this reason, at the end of the procedure, each untreated individual can be:

a) matched to only one treated individual.
b) matched to more than one treated individual.
c) unmatched.

To be effective, the matching should balance the characteristics across the treated and respective matched comparison groups. To evaluate whether this objective has been achieved, the results of the matching can be explored by inspecting the distribution of the propensity scores in the treated and matched comparison groups. These should appear similar. Observable differences should raise concerns over the success of the match. The comparison of the summary statistics of the covariates used for the matching between the treated and matched groups is another important indicator of the degree to which the matching has been successful in balancing.

4. Data

To assess the impact of “Fast-start Finance”, we use the AidData Research Release 2.1 database. It collects and provides information on development finance making them more accessible and helping scholars and policymakers seeking to better assess development investments and results. One of the main sources of climate data on AidData funds is the Credit Report System database, managed by the OECD's Development Assistance Committee (DAC) which has been collecting information on international aid since 1960. A specific section of the database, named “Aid activities targeting Global Environmental Objectives”, contains bilateral commitment data on: i) aid in support of environment sustainability, ii) aid to biodiversity, iii) climate change mitigation, iv) climate change adaptation and v) desertification drawn from the Development Assistance Committee Creditor Reporting System (CRS) database.[4]

We use the funds for energy generation and supply by renewable sources and the flows of funds targeted at biosphere protection.[5] To analyze the effectiveness of climate funds and assess the impact on the environmental performance, we use a dataset of 149 countries (see Appendix A1). It considers the totality of countries eligible to receive funds according to the OECD's Official Development Assistance (ODA) list. Dataset includes countries that have received funds in 2010 (treated – 83 counties) and those that did not receive funds (untreated – 66 countries). Explanatory variables can be grouped as target and control indicators.

Treated countries before and after receiving the treatment are similar to their matched untreated countries in terms of the control variables. Nevertheless, to test if the program is been successful, we want to verify if after the treatment have a different behavior in terms of the target variables because the former (control variables) are not affected by climate funds whereas the latter (target variables) are. These differences, under the hypothesis that, without the funds (received two years before), the treated countries would be similar to the untreated countries, also in terms of the target variables, are quantified and interpreted as the effects of the policy (Rajeev and Sadek, 2002).

Among the target variables, we include:

i) the share of renewable energy in the total energy generated (*shren*);
ii) GDP per capita (*gdp*);those for which climate funds aim to reduce:

those for which climate funds aim to increase:

i) CO_2 per capita emissions (*co2*), proxy for total GHG emissions; and
ii) the share of fossil energy in the total energy generated (*shfoss*).

In the group of control variables, we consider those typically indicated by the previous literature (see, e.g., Marques et al., 2011) as key factors that drive countries toward increasing generation from renewable energy sources: electricity consumption, the oil supply, energy intensity, the female population and the population growth rate.

The total electricity consumption (*elcons*) is commonly assumed as a proxy for the level of economic development. The relationship between GDP per capita and energy consumption per capita has been extensively

[4] By AidData dataset we extrapolate data on funds destined to developing countries related to “Energy generation and supply” (code 23030 – Power generation/renewable sources) and to “General environmental protection” (code 41020 – Biosphere protection).

[5] Both types of financial flows are among the aid directed at climate change both in terms of climate adaptation and in terms of climate mitigation.

analyzed over the year, considering time series data. Results of this research demonstrates the presence of a short run and/or long run causality. Countries are able to better promote investments in renewable energy sources by employing different forms of grants and incentives (Romano et al., 2017).

Moreover, higher incomes countries can imply additional electricity consumption, that is, from available fossil generation, to maintain citizens' perception of their quality of life (Marques et al., 2011).

Other studies, in which cross sectional dataset are used show that the relationship between energy consumption and economic growth yield conflicting results for both developed and developing countries. In these cases, the relationship becomes weaker and electricity consumption can be considered as expression of other variables such as: energy supply, political and economic history, political arrangement, and culture and energy policy (see, e.g., Chen et al. (2007) for an analytic review of the papers that study this relationship).

Since economic growth is a target variable, and since literature does not express an unanimous opinion concerning the relationship between electricity consumption and GDP we conduct a simple preliminary analysis. Results[6] indicate the absence of correlation suggesting to include both indicators in the counterfactual analysis. The increase in energy consumption can lead policymakers to build new RES power plants, taking advantage to reach this aim through the climate funds.

The total oil supply (*oil*), measured in terms of the production of crude oil (including lease condensate), natural gas plant liquids and other liquids, and the gain in refinery processing, is included in the group of control variables because, with this indicator, we can control for lobbying effects (see, e.g., Marques et al., 2011; Marques and Fuinhas, 2012). In the countries where these resources are used intensively we expect that the climate funds are less attractive. In this group, we also include energy intensity (ei). As argued by Romano et al. (2017), more developed economies are also oriented toward production efficiency improvement and low-energy intensity, and for these reasons, the ratio between energy consumption and GDP can be considered a proxy for technological and economic progress. Because our dataset contains mainly developing countries, which are more oriented toward the use of traditional energy sources, a poor propensity for the usage of climate funds by countries is expected. The share of the female population (*female*) is included because it has been shown that women have stronger preferences for environmental issues and protection (see Zhao et al., 2013). Thus, this variable can represent a proxy for the population's preference for a greener policy management, i.e., an indicator of a 'green sentiment' and, consequently, an indicator of the feeling for the population regarding the use of climate funds. Furthermore, we expect that, to meet the global demand for energy, countries with a high population growth rate (*popgrow*) may be more interested in climate funds.

The definitions, data sources and descriptive statistics of the target and control variables for the sample (149 countries: treated and untreated) are reported in Table 4.1.

5. Empirical results

The main purpose of climate funds is to help developing countries promote green growth. Our analysis can help illuminate what has been achieved during the "fast-start finance" period and to draw lessons for international climate finance in the years ahead, when the GCF should produce its effects.

[6] Before to include electricity consumption in the set of control variables, we addressed this point computing both the simple correlation between it and GDP, and running a regression where electricity is regressed on GDP. The simple correlation between the two variables is equal to 0.0171; the per capita gdp coefficient of the regression is not significant (0.0003 with p-value of 0.8358). The results indicate the absence of correlation in our data.

Table 4.1
Data: definitions, descriptive statistics and sources.

Label	Variable	Unit	Mean	Std. Dev.	Min	Max	Source
Control Variables							
elcons	The electric consumption (log of) is the electric power consumption equal to the sum of total net electricity generation and electricity imports net of the electricity exports and electricity transmission and distribution. losses	Billion Kilowatt-hours	61.72	324.34	0.02	3781.54	The U.S. Energy Information Administration (EIA)
oil	Total Oil Supply includes the production of crude oil (including lease condensate), natural gas plant liquids, and other liquids, and refinery processing gain[a].	Thousand Barrels Per Day	464	1429	−0.54	10,908	
ei	Energy intensity using purchasing power parities is calculated by dividing the data on total primary energy consumption in quadrillion British thermal units for each country and year by the gross domestic product using purchasing power parities in billions of (2005) U.S. dollars for each available country and year	Btu per Year 2005 U.S. Dollars (PPP)	6759	6215	199	50,976	
female	Female population is the percentage of the population that is female	% of total	49.74	3.48	24.65	54.31	World Bank (World Development Indicators)
popgrow	Population growth rate	annual %	1.70	1.56	−2.10	10.40	
Target Variables							
shfoss	Fossil Fuels electricity generation consists of electricity generated from coal, petroleum, and natural gas.	% of total	0.66	0.34	0.00	1.00	The U.S. Energy Information Administration (EIA)
shren	Renewable electricity generation includes generation from hydroelectric and not hydroelectric sources	% of total	0.33	0.34	0.00	1.00	
co2	Per capita carbon dioxide emissions including Land-Use Change and Forestry	Metric tons	4.09	6.49	0.03	46.7	World Bank (World Development Indicators)
gdp	GDP per capita based on purchasing power parity (PPP).	Constant 2011	12,367	16,274	698	127,670	

[a] Occasionally, the result for a product is negative because total disposition of the product exceeds total supply. Negative product supplied may occur for a number of reasons: (1) product reclassification has not been reported; (2) data were misreported or reported late; (3) in the case of calculations on a PAD District basis, the figure for net receipts was inaccurate because the coverage of inter-PAD movements was incomplete; and (4) products such as gasoline blending components and unfinished oils have entered the primary supply channels with their production not having been reported, e.g., streams returned to refineries from petrochemical plants. Petroleum Supply Monthly (PSM) explanatory notes https://www.eia.gov/petroleum/supply/monthly/pdf/psmnotes.pdf.

Table 5.1
Coefficients and goodness of fit statistics of the probit propensity score model (std. errors are in parenthesis).

Variable	Coefficient
intercept	1.5527 (5.9841)
log (elcons)	0.3752*** (0.0826)
oil	−0.0003** (0.0001)
log (ei)	−0.4111** (0.1755)
female	0.0207 (0.1047)
popgrow	0.8419*** (0.2756)
log (elcons)^2	0.0225 (0.0249)
popgrow^2	− 0.2019*** (0.0775)
Loglikelihood	− 73.7389
Pseudo R^2	0.3185
MF R^2	0.2792

Significance of coefficients: '***': p-value ≤ 0.01; '**': p-value ≤ 0.05; '*': p-value ≤ 0.1.

5.1. Propensity scores matching and balance

The coefficients of the propensity score probit model are reported in Table 5.1. They respect the expected signs and are in line with the results of several recent analyses of the determinants that drive policy-makers in energy policy decisions (see, e.g., Marques and Fuinhas, 2012; Aguirre and ibikunle, 2014).

Climate funds are more attractive for countries characterized by increasing population growth rates (*popgrow*), even though at decreasing marginal rate (because the second order coefficient is negative), and high levels of energy consumption (*elcons*). In these countries, most likely, the growing population, leads to intensified agricultural practices, an increase in land use and deforestation, industrialization and the associated energy use of fossil sources. These factors that characterize them can explain the relationship between population growth rates and funds. There is no empirical evidence that climate funds are attractive to countries where the female population composition (*female*) is higher, probably because in the developing countries the women feeling for environmental issues are less consolidated. By contrast, oil-exporting countries (*oil*) and those that are more oriented toward the use of traditional energy sources (high energy intensity, *ei*) prove to be more resistant to these types of policies in support of renewable energy generation because they imply structural changes in their industrial structures and economic systems that are generally well-developed. The results of the probit model confirm several consolidated issues and it is an important starting point for the next step of the work, which concentrates on the analysis of the impact of the funds on the countries that have obtained them. To valutate the estimated model we report the value of the *maximum likelihood pseudo r-squared* (Pseudo R^2) that explains the proportion of the variance of the latent variable that is explained by the covariates and the value of the *McFadden r-squared* (MF R^2) which is an alternative, known as "likelihood ratio index". This test, comparing a model without any predictor to a model including all predictors, is defined as one minus the ratio of the log likelihood with intercepts only, and the log likelihood with all predictors (McFadden, 1973).

Moreover, the matching performed using the fitted values of the model (the propensity scores) ensures that the similarities between matched countries are respected: the average values of the control variables of the untreated countries are not significantly different from those of the countries to which they have been matched (Table 5.2 column 2). The matching is obtained using the nearest neighbor (1) algorithm that provides a one-to-one matching.

Table 5.2
Tests of balance: similarities of means of the control variables before and after matching.

	Before matching	After matching
log (elcons)		
Mean Treated	2.2136	2.2136
Mean Untrated	0.7167	2.2912
p-value	0.0001	0.7083
oil		
Mean Treated	407.1200	407.1200
Mean Untrated	535.0500	220.1200
p-value	0.6155	0.1324
log (ei)		
Mean Treated	8,4311	8,4311
Mean Untrated	8,5444	8,6231
p-value	0,4435	0,1874
female		
Mean Treated	50.2560	50.2560
Mean Untrated	49.0910	50.3640
p-value	0.0697	0.4943
popgrow		
Mean Treated	1.6457	1.6457
Mean Untrated	1.7591	1.7338
p-value	0.6837	0.5587
log (elcons)^2		
Mean Treated	9.6207	9.6207
Mean Untrated	5.8147	8.6408
p-value	0.0162	0.3964
popgrow^2		
Mean Treated	3.6393	3.6393
Mean Untrated	7.3523	4.0908
p-value	0.0709	0.3631

Different matching algorithms have been tested before choosing the nearest neighbor (1), among these: the inverse variance distance that uses a one to many matching rule, and the genetic matching that finds the optimal balance with a genetic search algorithm that determines a weight or each covariate. We have chosen the nearest neighbor (1) algorithm because the other algorithms, even if ensure that more untreated observations have been matched, penalize the bias in terms of large differences between treated and untreated on their observed covariates.

Moreover the matching is obtained setting the caliper threshold equal to =0.25 (Austin, 2011). The caliper is a measure of tolerated difference between matched countries in a "non-perfect" matching. Setting it to the level of 0.25 means that all matches not equal to or within 0.25 standard deviations of each covariate in X are dropped. Setting this caliper threshold we impose a form of common support to increase the confidence that the condition holds.

Additionally, the distribution of the scores of treated and untreated countries (Fig. 5.1) confirms that the propensity score model is able to capture the similarities between the two groups.

6. Discussion

We tested several specification models. The choice of the variables in the final specification model is been driven by two main criteria: i) the quality of the balance; ii) the goodness of fit of each probit model estimated. The detailed results of the path that leaded us at the final specification are reported in Appendix A2.

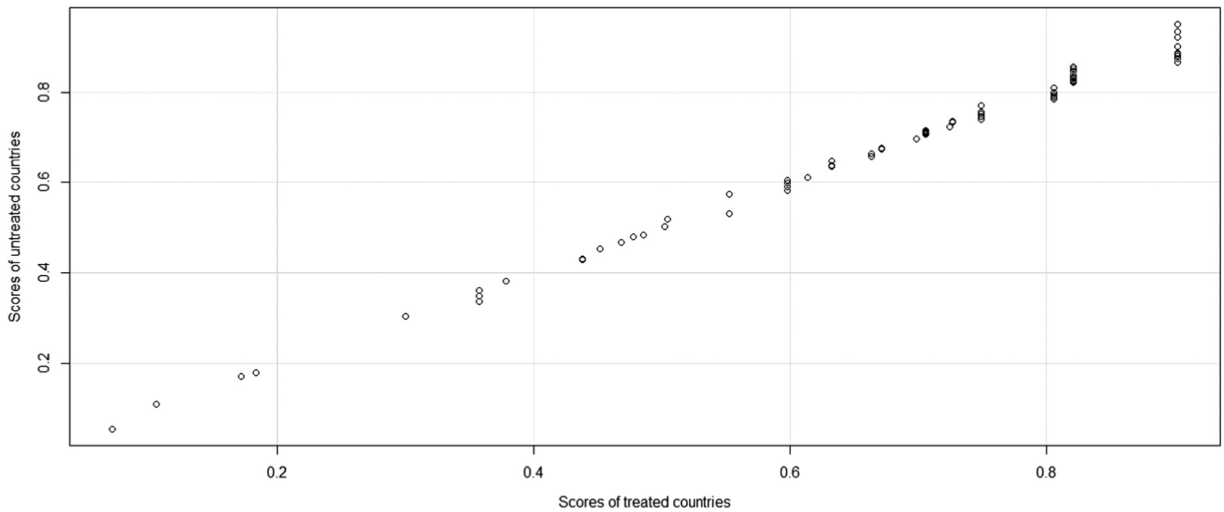

Fig. 5.1. Scatterplot of propensity scores of treated and untreated countries.

6.1. Estimating the effectiveness of climate funds: the treatment effect

The treatment effect on treated (ATT) represents a comparison between the observed values and the expected values of the target variables for the treated countries if they had not participated in the treatment. Countries that have received funds, in fact, are similar, in terms of the control variables, to the countries that have not received funds to which they have been matched. However, they are different in terms of the target variables, and the basic hypothesis is that this difference is due to the treatment. Table 6.1 reports the values of the estimated ATT.

In terms of CO_2 emissions (*co2*), without the funds, there would have been no differences between treated countries and their similar matched countries. Instead, the significant reduction of about 2.8 metric tons in the CO_2 per capita emissions of treated countries is a result that is in line with the theoretical background of this paper and with the global climate finance architecture. This result suggests that climate finance mechanisms, in fact, are useful to enhance the efforts to reduce emissions. However, although expected, this result is helpful in quantifying the effects of the main aim of this policy.

Focusing on per capita GDP (*gdp*), we observe another difference between treated and untreated countries. On average, the GDP of countries that have received funds increases approximately 1340 USD with respect to that of the counterfactual part. This result confirms those of several recent studies on the positive effects of climate financing on the economies of developing countries (Jakob et al., 2015; Ellis et al., 2013), with renewable energy being a crucial component for the economic growth of developing countries (Saidi and Ben Mbarek, 2016).

Table 6.1
Average treatment effects on treated (std. errors are in parenthesis).

Variable	ATT
shren	0.1872^{**} (0.0879)
shfoss	-0.1670^{*} (0.0864)
co2	-2.8205^{**} (1.1139)
gdp	1344.3^{**} (686.66)

Significance of coefficients: '***': p-value ≤ 0.01; '**': p-value ≤ 0.05; '*': p-value ≤ 0.1.

Observing the estimation results, we note that treated countries have, on average, a share of energy produced by renewable sources (*shren*) that is significantly higher with respect to their similar untreated countries by approximately 19%. Complementarily, the share of energy produced by fossil fuel (*shfoss*) is significantly lower, on average, by approximately 17% with respect to the counterfactual part of countries. This important result suggests that climate finance can help countries increase investments in RES generation and can substitute for fossil power generation. Moreover, this result indicates that the climate funds help to change the electricity basket generation, increasing the share of RES generation in place of fossil fuel generation.

6.2. Explaining the substitution effect between fossil and RES generation

To better investigate the last issue that emerged in light of the results of the treatment effect, we propose a supplementary detailed analysis based on the utility of fossil and renewable generation. The substitution effect on the optimal choice of Renewable (θ_1) and Fossil (θ_2) generation is a disputed point in the literature. A recent work by Salim et al. (2014) using a panel dataset of OECD countries shows that there is a long-term equilibrium relationship among non-renewable and renewable energy sources. Other studies (see, e.g., Al-mulali et al., 2014) show that countries that increase their investment in renewable energy projects increase the role of electricity consumption from renewable sources compared to that from non-renewable sources.

Our hypothesis is that the substitution effect revealed in terms of the sources of energy generation induces not only a reduction in CO_2 emissions but also, as indirect effect, an increase in electricity generation and, consequently, an increase in their utility.[7]

For the sake of simplicity, we consider that the utility of electricity generation can be a function of RES (θ_1) and fossil generation (θ_2), U (θ_1, θ_2).

This utility function represents the level of satisfaction obtained by a

[7] Previous studies of the application of utility functions to energy generation have explored how they can be used to quantify and manage the tradeoffs in the production processes between emissions and energy consumption (Sims et al., 2003; Noblet et al., 2015; Pohekar and Ramachandran, 2003). They are more concerned with issues such as costs and investments. In this work, we want to analyze the tradeoff between fossil and RES generation.

country as a function of its capacity to generate power; thus, the level of utility U is measured in terms of electricity generation. The reason for this choice is based on the assumption that, in the decision on the amount of electricity generation, policymakers examine the tradeoff between the necessity to support economic activities and the concerns for preserving natural resources and the environment. The hypotheses underlying this assumption are that, in managing the tradeoff, policymakers are faced with a direct choice regarding how to compose the basket of sources of energy to generate electricity: fossil sources or renewable sources. The former are consolidated, less expensive and more established to support the productive processes but have a stronger environmental impact, whereas the latter require investments and structural resizing but have a higher degree of sustainability (Weigelt and Shittu, 2016; Nazari et al., 2015).

The optimal pair of function settings (θ_1, θ_2) is that for which the transformed utility U is maximized under the budget constraint:

$$Y = C_1\theta_1 + C_2\theta_2 + (\bar{F}\theta_1|\varepsilon X) \tag{6.1}$$

where C_1 and C_2 are the unit costs of energy generated by renewable and fossil sources, respectively, and $\bar{F}$ is the average amount of each climate funds. Consequently, developing countries that are involved in reducing, with a target ε ($0 < \varepsilon \leq 1$), their GHG emissions (X) to enforce renewable energy generation projects can benefit from various instruments by using different and multiple policies (Romano et al., 2017). For untreated countries, i.e., countries that have not received funds, $F = 0$; for treated countries, the higher the ε is, the greater the amount of $\bar{F}$.

Maximization can be obtained through the Lagrange multiplayer method:

$$L = U(\theta_1,\theta_2) + \lambda(Y - C_1\theta_1 - C_2\theta_2 - [\bar{F}\theta_1|\varepsilon X]) \tag{6.2}$$

and its partial derivatives, under the assumption of a multiplicative form of energy utility functions

$$U = \theta_1^{\alpha}\theta_2^{\beta}$$

are:

$$\frac{\delta L}{\delta\theta_1} = \alpha\frac{U(\theta_1, \theta_2)}{\theta_1} - \lambda(C_1 - [\bar{F} \mid \varepsilon X]) = 0$$

that is,

$$U(\theta_1, \theta_2) = \frac{\theta_1}{a}\lambda(C_1 - [\bar{F} \mid \varepsilon X]) \tag{6.3}$$

and

$$\frac{\delta L}{\delta\theta_2} = \beta\frac{U(\theta_1, \theta_2)}{\theta_2} - \lambda \quad C_2 = 0$$

that is,

$$U(\theta_1, \theta_2) = \frac{\theta_2}{\beta}\lambda C_2 \tag{6.4}$$

Eq. (6.3) indicates that, for untreated countries, which have $\bar{F} = 0$, only the unit costs of renewable energy, C_1, influence the choice regarding the amount of θ_1, for determining the optimal level of electricity generation. For treated countries, the amount of $\bar{F}$, related to the GHG emissions reduction targets, is also considered. In particular, for these countries, the greater the emissions reduction target is, the higher the amount of funds, $\bar{F}$, and more attractive become the RES in determining the optimal level of electricity generation.

Under the assumption of a multiplicative form of energy utility functions (see, e.g., Silva et al., 2015):

$$U = \prod_{j=1}^{n} k\theta_j^{u_j}$$

where k is an overall scaling constant and $u_j(.)$ is the utility function operator for each attribute j. The country's utility value can be represented by a linear logarithmic function:

$$\log(U) = \log(k) \quad + u1\log(\theta_1) \quad + u2\log(\theta_2) \tag{6.5}$$

The parameters of Eq. (6.5), i.e., k, u_1 and u_2, represent the elasticities of θ_1 and θ_2 and have been estimated by Ordinary Least Squares (OLS)[8] both for the function of untreated countries (66 observations) and for the function of treated countries (83 observations). They are all significant (at the level of 99.9%) different from 0 as their differences (Table 6.2).

In fact, for the countries that have received climate funds, the elasticity of θ_1 is higher with respect to the elasticity of θ_2. The result for the countries that have not received climate funds is the opposite. Fig. 6.1 reports the representation of the elasticities for treated and untreated countries.

The figures lead us to confirm that both estimated utility functions respect the theoretical assumption of Eq. (6.3). Countries that receive climate funds are incentivized to promote the use of energy by renewable sources for the higher benefits obtained in terms of electricity generation. In fact, in these countries, a unit increase in the use of energy by renewable sources implies a growth in the utility that is higher than what would have occurred if the same increase concerned the use of energy by fossil sources. The increasing deployment of RESs has positive impacts in a number of key areas such as climate change mitigation, by reducing the impact of anthropogenic activities on the atmosphere, and energy security, by reducing the demand for imported fossil fuels and energy efficiency.

Table 6.2
OLS estimation of coefficients of the utility function (std. errors are in parenthesis).

	Treated	Untreated
RES generation (u_1)	0.3834^{***} (0.0346)	0.2272^{***} (0.0429)
Fossil generation (u_2)	0.2830^{***} (0.0375)	0.5138^{***} (0.0528)
F	157.9^{***}	68.84^{***}
Adjusted R^2	0.7979	0.6761
t-test on differences between coefficients – $H_0: \beta_{Treated}-\beta_{Untreated} = 0$		
RES generation (u_1)	4.5180^{***}	
Fossil generation (u_2)	-6.1626^{***}	

Significance of coefficients: '***': p-value ≤ 0.01; '**': p-value ≤ 0.05; '*': p-value ≤ 0.1.

7. Conclusions and policy implications

Climate funds aim to promote green growth in developing countries and they are partnering with a growing variety of international and developing country-based institutions. The number of implementing agencies has expanded from the three original organizations to approximately 40 institutions (Nakhooda and Norman, 2014): regional development banks, international organizations, developing country ministries, trust funds and Non-Governmental Organizations (NGO).

[8] Elasticities estimations are based on an iterative algorithmic procedure. It is reported in the Simulation Code and Data.

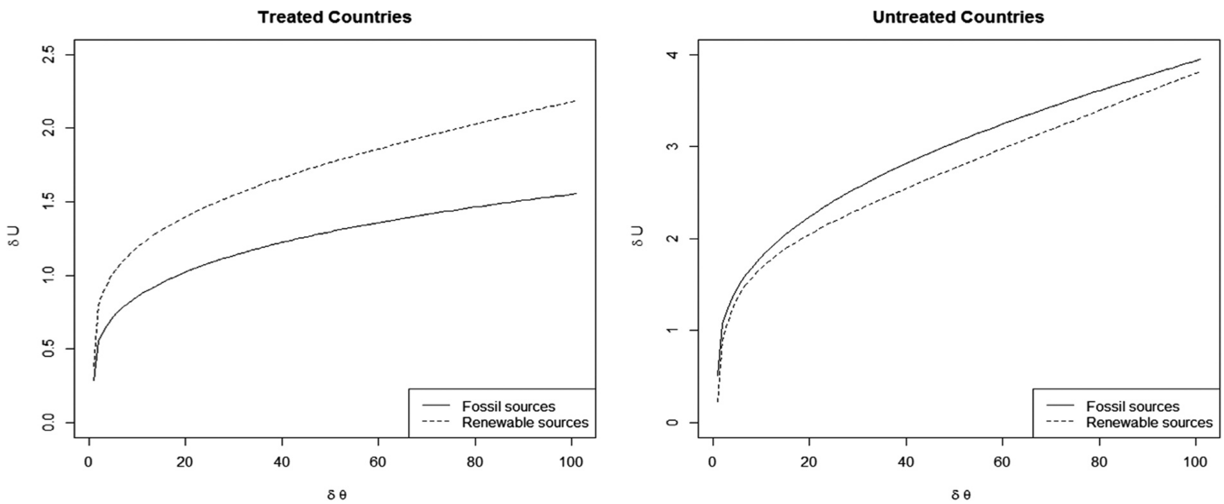

Fig. 6.1. Marginal effects for treated and untreated countries.

Moreover, because their official scope is to help the institution to limit climate change, in this paper, we have derived a model to evaluate the effectiveness of a policy intervention based on the differences, over a given policy evaluation horizon, between the post-intervention realizations of the target variables and the associated counterfactual outcomes.

The results obtained in this paper provide clear indications on the effectiveness of climate funds in promoting the green growth. The results show that funds have been devoted to enhance energy efficiency and sustainability: the recipient countries, in fact, reduced their GHG emissions respect to their similar counterparts. The factors that explain this empirical result are the positive consequence of the policies implemented in the last years in which the need to reach the targets imposed by the climate finance leaded them toward an increasing attention for environmental issues.

Moreover, the results show a decrease in the shares of electricity generated by fossil fuels and an increase in RES generation. In particular in these countries, we observe that the decrease of the generation of energy by fossil sources is balanced by the increase of the generation of RES. This sources' substitution can be identified in the factor used into the electricity production processes: "renewable energy sources in place of the fossil ones".

The increase in GDP per capita occurs in the recipient countries, with respect to the counterfactual part. Climate funds can be considered helpful instruments to promote the path towards a sustainable energy system, based on a high share of RES generation, for developing countries.

Clearly, "all that glitters is not gold", although countries have had several years to put in place policies on the ground to help get them to their targets, few have done so. A ranking published by the environmental group Climate Action Network[9] shows this is the case even in Europe, the world's supposed leader in fighting climate change. Also the recent announcement to pull the U.S. out of the Paris Agreement of President Donald Trump may frustrate all the progresses made in the recent years by U.S. toward a more sustainable environmental policy. Furthermore, no steps ahead have been made by the recent COP24 Katowice summit which final resolution aims to deliver the Paris goals of limiting global temperature rises to well below 2^{C}. The reason for this is that the post-Paris agreements have not changed the base plant in terms of emissions and countries postpone the most important policy decisions to reduce their emissions. The environmental policies take on average a long time to produce their first effects, as things stand it would be desirable for developed countries to broaden and refinance their energy policies. As their emissions are now roughly equal, so as not to exacerbate inequalities, the participation of developing countries is necessary to achieve the global objectives of atmospheric stabilization. For this reason, the allocation of the per capita target rather than the overall target of each individual state should be widely recognized to define a fair long-term target, so that national responsibilities should be deducted by summing up the excess emissions of all "high-emission" individuals in a country without unjustly mortifying economic operators operating using low-emission technologies.

In order to ensure the efficient funding allocation, policy makers have to regularly monitor the achieved results of financed projects. Our results could support the Ad Hoc Working Group on the Paris Agreement (APA) in monitoring the progresses made to reach the goals of the climate funds. Moreover, the findings provide a starting point to plan environmental policies to be undertaken in preparation to the full implementation of the Paris Agreement. The analysis carried out shows that the beneficiary countries have increased the share of electricity from renewable sources and have reduced the share of electricity from fossil ones, finding it more useful and advantageous to replace them with renewable ones. However, funding should be better targeted. For the further researches our aim is to identify the countries that had greater benefits from climate funds, both in terms of share of clean electricity generated and GHG emission reductions, and in GDP growth, identifying the socio-economic characteristics of these countries (the determinants of countries' performance). This could make it possible to select similar countries based on these characteristics and to provide the latter similar green funding in terms of projects (and amount).

[9] www.climate-change-performance-index.org.

Appendix A1

The analyzed countries (treated and untreated) are reported in Table A1.

Table A1
Countries.

Treated	Untreated
Afghanistan	Albania
Algeria	Antigua & Barbuda
Angola	Bahamas The
Argentina	Bahrain
Armenia	Barbados
Azerbaijan	Belize
Bangladesh	Bhutan
Belarus	Brunei
Benin	Bulgaria
Bolivia	Burkina Faso
Bosnia and Herzegovina	Burundi
Botswana	Central African Republic
Brazil	Chad
Cambodia	Comoros
Cameroon	Cote d'Ivoire
CapeVerde	Croatia
Chile	Cyprus
China	Djibouti
Colombia	Dominica
CostaRica	Equatorial Guinea
Cuba	Estonia
Dominican Republic	Fiji
Ecuador	Gabon
Egypt	Gambia The
ElSalvador	Georgia
Eritrea	Grenada
Ethiopia	Guinea
Ghana	Guinea-Bissau
Guatemala	Guyana
Haiti	Hungary
Honduras	Iraq
India	Israel
Indonesia	Jamaica
Iran	Kiribati
Jordan	Korea Dem. Rep.(North)
Kazakhstan	Kuwait
Kenya	Latvia
Kyrgyzstan	Liberia
Laos	Libya
Lebanon	Lithuania
Lesotho	Macedonia FYR
Madagascar	Malta
Malawi	Mauritania
Malaysia	Mauritius
Maldives	Moldova
Mali	Oman
Mexico	Qatar
Mongolia	Russian Federation
Montenegro	Saint Kitts and Nevis
Morocco	Saint Lucia
Mozambique	Saint Vincent and Grenadines
Namibia	Samoa
Nepal	Saudi Arabia
Nicaragua	Seychelles
Niger	Sierra Leone
Nigeria	Singapore
Pakistan	Solomon Islands
Panama	Sudan
Papua New Guinea	Suriname
Paraguay	Swaziland
Peru	Togo
Philippines	Trinidad and Tobago
Rwanda	Turkmenistan
Sao Tome and Principe	United Arab Emirates
Senegal	Uzbekistan
Serbia	Zimbabwe
South Africa	
Sri Lanka	
Syria	

Table A1 (*continued*)

Treated	Untreated
Tajikistan	
Tanzania	
Thailand	
Tonga	
Tunisia	
Turkey	
Uganda	
Ukraine	
Uruguay	
Vanuatu	
Venezuela	
Vietnam	
Yemen	
Zambia	

Appendix A2

The choice of the final probit model occurred after tested some specifications. Among those with optimal balance (2, 5 and 6), i.e. those whose control variables of the untreated countries are on average not significantly different from matched countries, we selected the model with the highest log-likelihood value (model 6). It is used to test whether the addition of a covariate is statistically merited; the higher values of the index indicate an higher probability to have the right distribution coefficients. Among the three selected models, comparing the log-likelihood values from the smaller (2) to the larger (6) a model improved occurs. All the detailed are reported in Table A2.

Estimation of model and all the analyses were done using Matching package (Sekhon, 2015) implemented in R statistical software. The package is available on the CRAN package repository (www.cran.r-project.org) while codes used to obtain reported results and all additional information useful to make research reproducible will be made available by the authors on request. Data employed are freely available from U.S. Energy Information Administration (http://www.eia.gov), World Bank (http://www.worldbank.org/) and AidData partnership foundation (http://www.aiddata.org/).

Table A2
Propensity scores probit models: after balancing *t*-test of equality of means and loglikelihood values.

	1	2	3	4	5	**6**	7
log (elcons)	ns	ns	ns	s	ns	**ns**	ns
oil	ns	ns	s	s	ns	**ns**	ns
log (ei)	s	ns	ns	ns	ns	**ns**	s
female	ns	ns	ns	ns	ns	**ns**	s
popgrow	ns	ns	ns	ns	ns	**ns**	s
popogrow^2		ns				**ns**	ns
log (elcons) popgrow*			ns				
log (elcons)^2				s		**ns**	ns
oil^2					ns		
log (elcons)^2 popgrow^2*							s
LLh	−81.5	−74.2	−81.5	−80.7	−81	**−73.7**	−73.6

ns: after matching *t*-test difference not significant (at 10% level); s: after matching *t*-test difference significant (at 10% level).

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